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Long-term effects of group-based agricultural support amid COVID-19 shocks in Nepal

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LONG-TERM EFFECTS OF GROUP-BASED AGRICULTURAL SUPPORT AMID COVID-19 SHOCKS IN NEPAL

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ABSTRACT

This paper examines the long-term effects of agricultural support in western Nepal and whether support enhanced farmers' resilience to coronavirus disease (COVID-19) disruptions. From 2014 to 2022, farmers received various combinations of training, input (such as fertilizer and seed) subsidies, asset support, and credit, delivered through agricultural groups by multiple programs. Many of these programs had objectives related to the improvement of agricultural commercialization, which raises the question of whether they made households more vulnerable or resilient to market disruptions. We apply two-way fixed effects regressions and inverse probability weighting to estimate impacts of support from a 1,521 household panel dataset of observations in 2014, 2018, and 2022, which encompasses variations in both program exposure and local lockdown severity. We find that support led to substantial improvements in crop productivity, value, sales, and income. Effects are largest for support including training, asset subsidies, or credit, and support focused on higher-value products. Support provided between 2018 and 2022 had large effects in offsetting the negative impacts of COVID-19 restrictions, whereas support provided up to 2018 had a persistent effect in improving resilience to COVID-19 shocks. Effects from both periods of support are progressive with respect to income.

Keywords: Nepal, matching grants, extension, asset transfer, agriculture, COVID-19, resilience

JEL codes: O13, Q13, Q16, Q54

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1 INTRODUCTION

In many developing countries, and especially in South Asia, agriculture is central to the livelihoods of rural populations. This is particularly so in Nepal, where 78% of households live in rural areas and depend on small-scale farming and remittances for their livelihoods (World Bank, 2025). The agriculture sector is dominated by subsistence production, with small, fragmented plots, low levels of investment, and limited use of improved technologies. These characteristics are exacerbated by Nepal's rugged terrain and weak infrastructure, which make transportation costly and access to markets difficult, particularly for households in remote mountain regions. These structural constraints have contributed to a persistent low-productivity trap. As a result, most farmers grow low-value cereals for self-consumption to ensure food security, with little marketable surplus or incentive to adopt productivity-enhancing practices (Tiwari et al., 2008).

Given these conditions, many rural households view agriculture as a survival strategy rather than a viable pathway to prosperity. Opportunities to generate surplus income or invest in modern inputs are limited, leading to continued reliance on migration for livelihood diversification. Each year, a substantial number of Nepali men and women migrate abroad for seasonal or long-term work, underscoring the limited economic potential of smallholder farming (Tamang et al., 2014).

In response to these challenges, the Government of Nepal and various development partners have implemented agricultural support programs aimed at transforming smallholder farming from subsistence-based production toward more commercial, market-oriented systems. These programs typically offer support in the form of subsidized inputs (such as improved seeds and fertilizer), productive assets, credit, and technical training to improve productivity and incomes. From 2014 to 2018, several major donor-funded initiatives also promoted the cultivation of high-value crops, particularly vegetables and fruits, as a pathway to commercialization (Raitzer and Batmunkh, 2022).

A distinctive feature of agricultural support in Nepal is that assistance must be channeled through formal agricultural groups, such as farmer groups or cooperatives.

This group-based approach is designed to reduce administrative costs, generate economies of scale in extension delivery, and avoid the perception of elite capture. In principle, these groups serve as a mechanism to ensure more equitable access to support and facilitate collective action, market linkages, and peer learning.

While the short-term benefits of such programs have been documented in various settings, their long-term effects on farmer behavior, market participation, and resilience remain uncertain, especially in the face of external shocks like the coronavirus disease (COVID-19) pandemic. It is important to understand whether programs intended to improve commercialization increased the exposure of farmers to market shocks and increased vulnerability, or, alternatively, whether they helped farmers be better prepared for the shocks.

The COVID-19 pandemic created a sudden and severe disruption to agricultural markets and rural livelihoods in Nepal. In 2020, national lockdowns restricted vehicle movement on major roads, closed physical markets, and limited the mobility of seasonal agricultural laborers (Miguel and Mobarak, 2022). These disruptions were particularly damaging in areas where farmers relied on perishable cash crops, needed access to distant markets, or depended on input supply chains that were abruptly severed.

Importantly, not all regions were affected equally. While some areas experienced prolonged and strict lockdowns, others were less disrupted, as a result of variations in enforcement or geography. This heterogeneity in exposure provides a unique opportunity to assess whether prior agricultural support helped farmers withstand or adapt to the shock. In particular, it raises key questions about the durability of program impacts and the extent to which earlier investments in inputs, training, and group-based support translated into greater resilience.

This paper contributes to the literature on agricultural transformation and resilience in low-income settings in three main ways. First, it provides rare evidence on the long-term effects of agricultural support programs in a subsistence-dominated context, using a four-year panel dataset that tracks farm outcomes before and after program implementation. Second, it examines how these effects evolved under the stress of an unanticipated systemic shock owing to COVID-19, leveraging geographic variation in

lockdown exposure to assess resilience. Third, it analyzes heterogeneity in program effectiveness across support types and across the outcome distribution, highlighting the role of targeting and program timing in shaping equitable impacts.

The remainder of the paper is organized as follows. Section 2 provides background on agricultural support programs in Nepal and the disruptions the COVID-19 pandemic caused. Section 3 reviews the existing literature on commercialization, resilience, and the long-term effects of agricultural interventions. Section 4 describes the data and key variables used in the analysis. Section 5 outlines the empirical strategy. Section 6 presents the main results, including average treatment effects, heterogeneity across support types and outcome distributions, and evidence on household coping strategies. Section 7 concludes with a discussion of policy implications.

2 BACKGROUND

Nepal's agriculture sector faces persistent structural challenges that constrain productivity, market access, and income generation for rural households. In response, the Government of Nepal and international development partners have implemented a series of agricultural support programs aimed at promoting commercialization and resilience among smallholder farmers. This section provides an overview of the agricultural context in Nepal, details the structure and implementation of the support programs under evaluation, outlines the theory of change that underpins their intended impacts, and describes how the COVID-19 pandemic affected agricultural production and farmers.

2.1 Agriculture in Nepal

Agriculture in Nepal is characterized by low productivity, persistent subsistence farming, and a challenging topographic and infrastructural environment. The sector has seen volatile and modest growth averaging 3.2% annually in the past decade, with yields of staple crops such as rice, maize, and wheat remaining well below regional averages (IFAD, 2021).

Most Nepali farmers operate on small and fragmented landholdings: over half of all farms are smaller than 0.5 hectares, and mechanization is limited owing to plot dispersion and the high cost of equipment relative to farm size. These constraints make it difficult for households to benefit from scale economies or adopt modern technologies (Paudel et al., 2023).

The situation is compounded by limited access to quality inputs, such as seeds, fertilizer, and irrigation, and weak rural infrastructure, particularly in the hill and mountain regions, where market access is poor and transport costs are high. Irrigation is limited: around 64% of farmers depend on monsoon rainwater, making them more vulnerable to rainfall variations and climate change (IFAD, 2021).

Given these constraints, the Government of Nepal has identified the commercialization of smallholder agriculture through the production of higher-value crops, improved market integration, and investment in productivity-enhancing as essential to raising rural incomes and strengthening household resilience (Government of Nepal, Ministry of Agriculture and Livestock Development, 2015). Yet the shift away from subsistence is slow, in part because of the structural and geographic barriers described above. Addressing these bottlenecks is critical to any sustained improvement in farmer livelihoods and rural economic development.

2.2 Support to Farmers via Groups and Cooperatives

To help smallholder farmers move toward commercialization, the Government of Nepal and multiple development partners, including the Asian Development Bank (ADB), the International Fund for Agricultural Development (IFAD), the United States Agency for International Development (USAID), and the World Bank, have implemented a series of agricultural support programs since around 2010 with a particular focus on poverty-affected provinces such as Karnali, Lumbini, and Sudurpashchim.¹

The unique aspect of agricultural support in Nepal is that all such support to farmers is channeled through registered farmer groups and cooperatives. Farmer groups must have

¹ Raitzer and Batmunkh (2022) provide an impact evaluation of these programs up to 2018.

a minimum of 25 members and be registered with the local government agricultural office (Provincial Agriculture Knowledge Centers). Cooperatives possess a larger membership and face more stringent registration criteria but they are permitted to engage in savings and credit activities. Fertilizers are only officially distributed by the Agriculture Inputs Company Limited via farmer cooperatives and groups according to the National Fertilizer Policy of 2009 (Gautam et al., 2022), and this policy remained in place until 2025.

A number of programs involving asset transfers in combination with other support used a matching grant modality, in which organized farmer groups (e.g., cooperatives, producer associations) submitted proposals to receive co-financing for productive assets. These proposals were scored, and, if selected, donors financed 50% of the capital requirements for the new activity in specific high-value crops and livestock if groups could raise the other half of the required funding. Groups were supported in preparing technical and financial proposals and, if selected, received funding for capital investments alongside training. Trainings typically covered improved agricultural practices, marketing, and financial literacy or business skills.

At least seven projects followed this model, including the World Bank's Agricultural Food Security Project (AFSP), Project for Agricultural Commercialization and Trade (PACT), and Rani Jamara Kulariya Irrigation Project; ADB's Raising Incomes of Small and Medium Farmers Project (RISMFP); IFAD's High-Value Agriculture Project (HVAP); USAID's Knowledge Based Integrated Sustainable Agriculture in Nepal (KISAN); and the Government of Nepal's Prime Minister Agriculture Modernization Project (PMAMP). While most provided some combination of training and physical inputs, project intensity varied, with differences in grant sizes (ranging from \$5,000 to \$200,000), value chains targeted, and institutional capacity building. Some projects explicitly discouraged overlap to avoid multiple support streams going to the same group.

Three of the above programs completed implementation in 2018. The ADB-funded RISMFP finished implementation in 2021, and a new follow-up project, focused on nut and fruit production in hilly areas of central and western Nepal, began implementation in

2022.² Two projects that have continued operating over the entire period are an irrigation improvement project in a limited geographic area of Tikapur (RJK) and USAID-funded market-oriented cereal production in Terai (KISAN I & II). The primary source of funding for farmer groups since 2018 has been the government's PMAMP and local municipality funding after the federalization process was completed in 2018. Federalization has allowed rural municipalities to control more of the funding to the local agriculture sector, rather than this being directly controlled by the central government in Kathmandu.

Participation in a program was contingent on membership in an eligible farmer group, such as a cooperative or producer association, operating within the target districts. These groups were required to submit collective proposals detailing their planned investments and co-financing arrangements. While the eligibility criteria varied slightly across programs, common requirements included formal group registration, a minimum period of operation, and alignment with the program's targeted value chains. Individual households could not apply independently; instead, access to support—whether assets, inputs, training, or credit—depended on the group's application being approved and on the internal allocation mechanisms within the group.

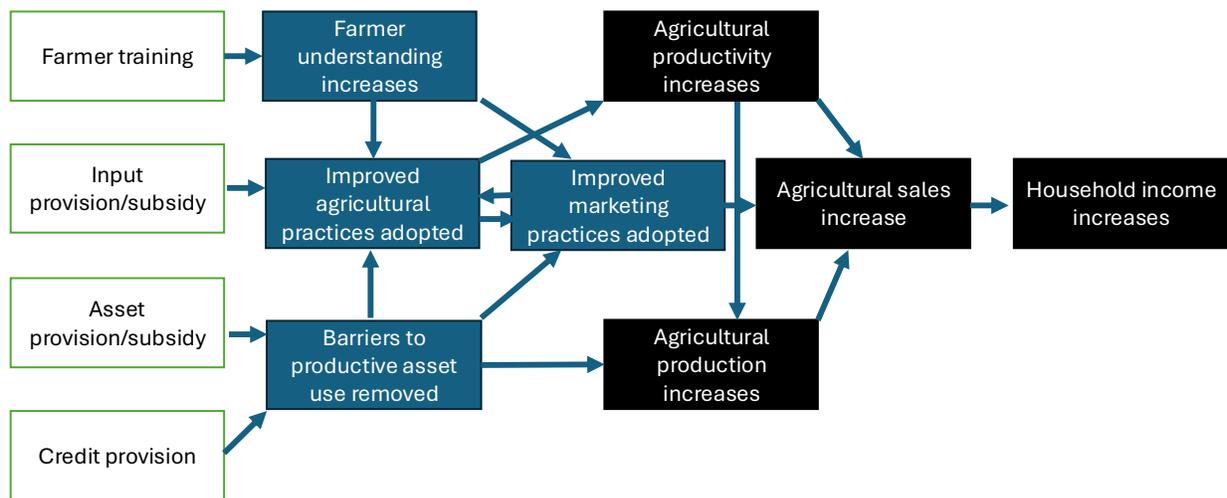
Although all programs aimed to raise agricultural income through increased high-value crop production and market sales, beneficiary-level exposure varied. Not all members of a supported group received the same type or amount of support, and the combination of support types (e.g., training, input subsidy, equipment, credit) differed widely across recipients. As such, understanding the effects of these support packages requires accounting for both the type and the intensity of assistance received.

2.3 Theory of Change

Agricultural support programs in Nepal aim to shift farmers away from subsistence cereal cultivation toward more commercial, market-oriented production, often of higher-value crops and livestock. To facilitate this transformation, these programs rely on several interlinked pathways, as illustrated in Figure 1.

² Nepal: Nuts and Fruits in Hilly Areas Project. Project No. 48218-006.

Figure 1: Theory of Change



Source: Authors' illustration.

Many programs provide farmer training to improve farmer understanding of new technological options for production or processes. This training is often accompanied by the provision of subsidized inputs or assets, so as to remove access or financing barriers to technological adoption. Farmer groups and cooperatives also often emerge from savings and microcredit groups, and thus offer credit that can help facilitate input or asset purchases. Selected programs provide marketing assistance via training, marketing facilities, or price information sharing. With improved production practices, agricultural productivity, and production rises, and this facilitates increased agricultural sales, which may be further enhanced by improved marketing practices. This greater commercialization is then intended to increase household income.

COVID-19 induced restrictions on mobility and markets may cause the mechanisms of improvement to be disrupted, or, alternatively, these pathways may have improved resilience to those shocks. For example, continued access to inputs necessary for improved techniques may no longer be possible. When markets are closed and movement is restricted, labor may be unavailable, and it may not be possible to sell products. Alternatively, improvement of these linkages via the supported programs may

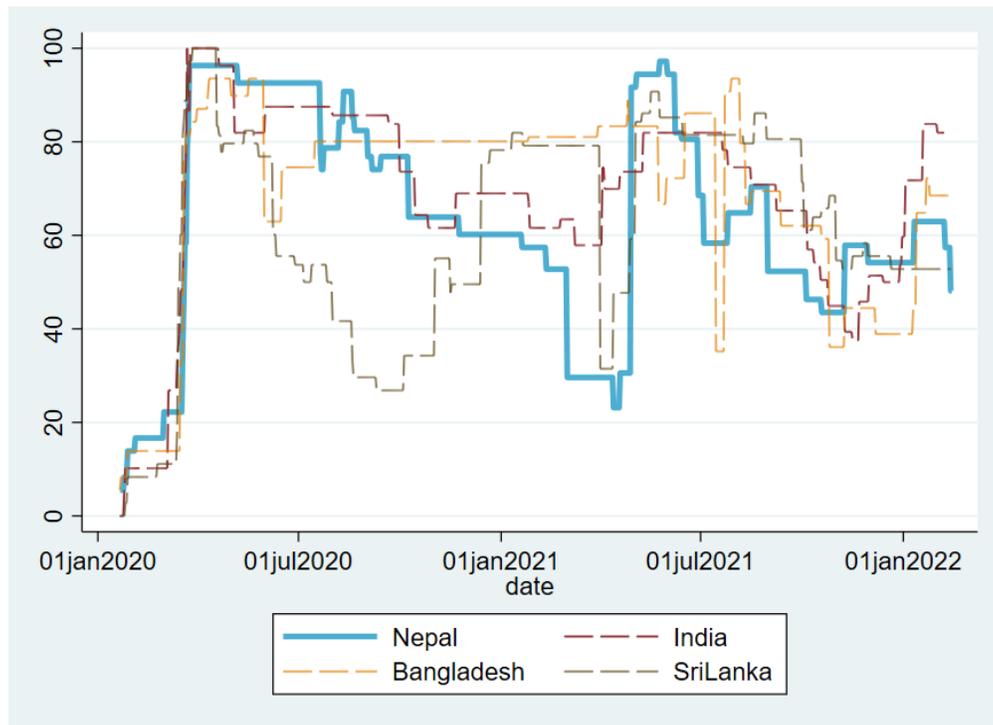
have helped farmers be better prepared. For example, input access channels may have helped farmers continue to utilize improved inputs when they became more scarce, and improved capacity may have helped farmers navigate a changing landscape for production and sales.

2.4 COVID-19 Lockdown Restrictions in Nepal

The COVID-19 pandemic occurred while a number of the agricultural support programs were ongoing, which substantially changed the context in which their activities unfolded. It introduced major disruptions to agricultural input and output markets, labor mobility, and household finances. This subsection summarizes the pandemic's effects on rural households and sets the stage for assessing whether program support helped farmers better withstand these shocks.

The COVID-19 pandemic prompted the Government of Nepal to impose a nationwide lockdown from 24 March to 21 July 2020 (Pandey et al., 2022). Although restrictions were later eased, they were intermittently reimposed in 2021 and 2022 in response to subsequent waves of infection. As Figure 2 shows, the overall stringency of Nepal's lockdown policies was comparable to that of the policies of neighboring South Asian countries. Importantly, farmers were generally allowed to continue fieldwork during planting and harvesting seasons, limiting disruptions to direct cultivation activities.

Figure 2: Coronavirus Government Stringency Index



Source: Oxford's Coronavirus Government Response Tracker.

The pandemic affected rural households primarily through two channels. First, repeated market and transport disruptions hindered the sale of agricultural products, particularly for commercial farmers reliant on input supply chains or perishable goods (Adhikari et al., 2021). Second, road closures and restrictions on inter-district movement also made it difficult to procure inputs, such as fertilizers and improved seeds, contributing to yield losses in some areas. In the early phase of the pandemic, movement restrictions also affected access to labor. Subsistence-oriented farmers, who relied less on purchased inputs or commercial sales, were relatively insulated from many of these disruptions.

3 PRIOR LITERATURE

This paper relates to three broad strands of literature: 1) group-based agricultural support programs in developing countries; 2) the impact of the COVID-19 pandemic on farming

systems; and 3) the long-term effects of support programs on household resilience and market integration.

3.1 Group-Based Agricultural Support Programs

Group-based agricultural support has been widely promoted by governments and development agencies as a mechanism to reach smallholder farmers at scale (Gugerty et al., 2019). Numerous studies find that participation in cooperatives is positively associated with greater use of inputs, access to extension and credit services, and increased productivity (Abebaw and Haile, 2013). However, these benefits are not uniformly distributed. Elite capture and exclusion of poorer farmers are persistent concerns (Banerjee et al., 2001), and a systematic review underscores that the effects of cooperatives on farmers' incomes are moderate, and market access effects remain mixed and highly context-dependent (Stewart et al., 2015).

Matching grants to farmer groups and cooperatives have become an increasingly popular policy tool in agricultural development over the past 2 decades (Sberro-Kessler, 2019). These programs aim to relax credit constraints and stimulate productive investment, yet rigorous evidence on their effectiveness remains limited (Campos et al., 2014; Sberro-Kessler, 2019). In Rwanda, matching grants helped small-scale producers overcome credit constraints with sustained effects (Hossain et al., 2022), while a study in Yemen found such programs had encouraged firms to undertake innovative activities they would not have pursued otherwise (McKenzie et al., 2017). However, implementation challenges—including low participation rates, delays, and difficulties with randomization—have hampered evaluation efforts (Campos et al., 2014). In contrast, microcredit programs targeted at individual farmers have generally shown limited impacts on input use, output, or commercialization (Nakano and Magezi, 2020).

3.1.1 Training

Conceptually, exposure to new technologies via training has the potential to permanently increase agricultural productivity, production, commercialization, and income.

Agricultural training programs are widely used to improve farmers' knowledge, productivity, and market engagement, but their effectiveness varies substantially by context and program design. Systematic reviews and meta-analyses find that training can raise technical efficiency by 4.8%–7.6% and increase income, employment, and entrepreneurship when combined with complementary support, such as access to land, finance, or infrastructure (Lampach et al., 2018; Maïga et al., 2020; Boye et al., 2024). However, rigorous evaluations underscore important caveats. For instance, a large-scale randomized trial in Armenia found no lasting impact of training on household income or agricultural practices (Blair et al., 2020), and studies from East Africa highlight that training alone often fails to drive change unless embedded within broader institutional support systems (Mgendi et al., 2021; van der Heijden, 2024).

Delivery mechanisms also matter. Farmer Field Schools (FFS), a common group-based approach, involve weekly sessions throughout the growing season, allowing participants to observe side-by-side comparisons of new and traditional practices (Bekele et al., 2013). Although effective in improving knowledge, FFS are resource-intensive. To reduce costs, many programs rely on “model farmers” to demonstrate improved practices on their own land. This approach increased adoption by 40% in Bangladesh (Emerick and Dar, 2021), but reach may be limited if model farmers lack ties to more marginalized households. A related study found that, while demonstration plots planted with both improved and local seed varieties raised awareness, they did not significantly increase adoption on average (Dar et al., 2022).

Crucially, information alone is often insufficient to change behavior. Farmers can be reluctant to adopt new technologies, such as new varieties or previously untried agronomic practices, without financial incentives. Duflo et al. (2011) show that behavioral nudges, such as offering time-sensitive fertilizer coupons to farmers unfamiliar with fertilizer use, can significantly boost uptake. These findings suggest that training must be paired with complementary inputs, subsidies, or behavioral design to shift practices at scale. This paper contributes to this literature by investigating whether productive asset provision via matching grants to groups facilitates downstream adoption

of improved agricultural technologies, such as fertilizer, irrigation, and greenhouses, at the household level.

3.1.2 Input Subsidies

Causal evidence from developing countries suggests subsidies for agricultural inputs can increase the use of improved seeds and fertilizer, leading to short-term gains in yields and farm income among beneficiary households (Jayne et al., 2018; Mamun, 2024). This is particularly the case when information asymmetries mean farmers are unaware of the benefits of higher input use or face adoption barriers, such as risk or credit access. Outside of these conditions, key challenges include poor targeting, leakage of benefits to wealthier farmers, and inefficiencies in implementation (Gemessa, 2022; Mamun, 2024). Conceptually, an input subsidy leads to an increase in input usage along the production function to a point where private marginal costs are equal to the output price, but social costs including the subsidy exceed the price. This means the marginal gain may be small relative to the cost, and the change in production may last only as long as the subsidy persists if markets are functional. Subsidies can also crowd out private input markets, undermining sustainability and reducing long-term effectiveness (Jayne et al., 2018).

3.1.3 Asset Support

Conceptually, support to assets can help farmers or farm groups to overcome barriers to mobilizing capital for “lumpy” or front-loaded productivity-enhancing investments with persistent effects. Evidence on the effects of asset support in agriculture comes in part from studies of the Graduation Approach for the Ultra Poor, which includes productive asset transfer (often of an agricultural asset) in a package together with technical training, financial literacy training, coaching, and consumption support. A series of different randomized controlled trials has found that these programs, inclusive of provision of livestock as assets as part of multidimensional support, have significant effects on household income and consumption (Banerjee et al., 2015). Matching grant programs for agriculture that include funding of an asset have been found to have

significant effects on productivity, production, and income (Hossain et al., 2022; McKenzie et al., 2017).

3.1.4 Commercialization Support

Many of the above forms of support take place under the aegis of “farm commercialization,” especially when they are complemented by activities to improve market linkages. The use of groups and cooperatives as a means to channel support is often intended to help foster economies of scale in marketing. The use of groups has a mixed track record. For instance, in Kenya, collective banana marketing through farmer groups yielded only modest price gains overall, and income benefits were limited to active members with contracts from buyers (Fischer and Qaim, 2012). Nevertheless, group membership facilitated knowledge sharing around cultivation, market demand, and input use. In Brazil, the Program for Strengthening Family Farming (PRONAF) significantly increased the probability that smallholder farmers would sell their output, especially when marketing support was combined with technical assistance. In contrast, standalone input provision (like seed distribution) had limited impact (Wesz Junior et al., 2024). Similarly, in Ethiopia, cooperative membership and participation in the Agricultural Growth Program increased commercialization and asset accumulation—but disproportionately so for already better-off households, raising concerns about equity (Teklewold, 2021; Tabe Ojong et al., 2022; Geffersa and Islam, 2024).

These mixed results highlight that commercialization support cannot be assumed to be a silver bullet and should be evaluated in each context. This is especially so as commercialization support has shown that it has the potential to increase risk from market disruptions. In Ghana, for example, failed value chain projects have left smallholders exposed to risk and loss, and even disrupted local livelihoods (Iddrisu et al., 2022). Across several African contexts, evidence shows that farmers with fewer resources or lower capacity often remain excluded from the gains of commercialization, unless interventions are explicitly tailored to their needs (Saha et al., 2022).

3.1.5 Long-Term Impact of Agricultural Support Programs

There is limited evidence on the long-term effects of agricultural support programs in developing countries, and findings remain mixed and context-specific. Short-term impacts of subsidies for inputs such as seeds and fertilizers are well documented, often showing increased input use, higher yields, and improved farm incomes. However, their longer-term effects on poverty reduction and sustainability are more uncertain. Poorly designed programs can suffer from inefficiency, corruption, and market distortions if not well targeted or phased out gradually (Mishra et al., 2024). That said, temporary subsidies may still generate lasting benefits by promoting learning and adoption of new technologies, with learning effects outweighing concerns about reduced willingness to pay in the future (Balew et al., 2025).

Evidence on farmer training and extension systems is mixed, but suggestive of effectiveness when delivered appropriately. On the whole, the literature shows a modest effect on productivity and technical efficiency, with larger effects driven by more participatory approaches (Lampach et al., 2018). However, delivering the participatory approaches at scale has also often proven problematic (Waddington et al., 2014).

Matching grant programs offer another avenue for support. Some of their benefits—such as reducing credit constraints during the program period—may be temporary, whereas others, like market linkages, financial inclusion, and technology adoption, can persist beyond the program's end (Sberro-Kessler, 2019). For example, in Uganda, an agricultural extension program led to durable behavioral change: farmers who initially accessed nongovernment organization-supported village-based supply networks eventually shifted to commercial suppliers, sustaining the gains after project closure (Fishman et al., 2022).

3.2 COVID-19 Effects on Farming

Lockdowns and mobility restrictions introduced in response to the COVID-19 pandemic had widespread effects on agriculture and food systems in developing countries. Most farmers in these contexts operate small plots, often under subsistence conditions, with

limited use of external inputs or market engagement. The literature highlights that the pandemic affected subsistence and commercial farmers in distinct ways (Morton, 2020).

For example, Adhikari et al. (2021) show that subsistence farmers in Nepal proved relatively resilient, relying on self-produced food and facing fewer disruptions in input supply. In contrast, commercial farmers—especially those dependent on perishable products and long supply chains—faced significant losses owing to transportation bottlenecks and market closures. Similar patterns emerged in studies from Central America, Mexico, Tanzania, and South Africa, where subsistence-oriented farmers were less exposed to market shocks and input shortages (Lopez-Ridaura et al., 2021; Tripathi et al., 2021; Adhikari et al., 2021).

However, this resilience did not extend to all groups. Already vulnerable populations, particularly women, marginalized communities, and residents of remote areas, faced heightened food insecurity and fewer coping mechanisms. These findings suggest that building stronger links between smallholders and markets, while ensuring inclusive and context-sensitive support, is essential to improving resilience to future shocks.

There is very little evidence on whether agricultural support programs helped mitigate the effects of COVID-19 market disruptions. Moreover, there is considerable uncertainty about whether prior support built resilience to the COVID-19 shocks. This paper contributes to this literature by examining whether the benefits of agricultural support programs persist over time, or whether they were eroded by COVID-related disruptions to agricultural value chains.

3.3 Hypotheses

Nepal's agriculture sector faces structural constraints, such as small and fragmented landholdings, high transaction and transportation costs, and limited access to formal credit and market information. To address these barriers, agricultural support programs provided training, productive assets, subsidized inputs, and credit to smallholder farmers through cooperatives and farmer groups. These interventions are expected to improve production outcomes by reducing input costs, facilitating technology adoption, and improving market participation.

The effects of support are expected to vary by type and intensity. Training is expected to increase the efficiency of input use and promote the adoption of improved practices. Inputs and assets can directly reduce production costs or expand production capacity. Credit can ease liquidity constraints, though it may not directly improve productivity unless paired with technical or material support.

The COVID-19 pandemic introduced a significant external shock that disrupted both input and output markets. These disruptions may have reduced the effectiveness of support programs, especially those requiring market access to realize returns (e.g., high-value crop production or more perishable horticulture). However, households receiving timely support may have been better equipped to withstand pandemic-related shocks.

Based on this conceptual framework, we test the following hypotheses:

1. **Main effects:** Households that received agricultural support—particularly training and input or asset provision—will experience increases in crop production value, crop and livestock sales, and total income, relative to non-beneficiaries.
2. **Differential effects by support type:** The magnitude of impact is expected to vary depending on the type of support received. Asset support is expected to have larger effects on income and sales owing to its potential to expand production capacity. Input support is expected to reduce production costs and improve short-run productivity. Training can potentially shift production possibilities frontiers and improve long term productivity through exposure to new technology.
3. **COVID-19 heterogeneity:** The positive effects of support are expected to be smaller in areas with high levels of market closure during the COVID-19 pandemic, especially for commercial outcomes like crop sales. However, beneficiaries in these areas may still fare better than non-beneficiaries in relation to coping with shocks.
4. **Persistence of effects:** Support received earlier (between 2014 and 2018) may have lasting impacts observable at endline in 2022, especially for durable investments such as assets and training, while short-term support like input provision may yield more transient effects.

4 DATA

This section describes the data sources and sampling strategy used to evaluate the impacts of agricultural support programs in western Nepal. We rely on three rounds of panel data collected from rural households, farmer groups, and settlements between 2014 and 2022. The sampling design enables comparison between program beneficiaries and similar households that did not receive support, while the panel structure allows us to track long-term outcomes before, during, and after implementation of the programs.

4.1 Study Sample

This evaluation focuses on four districts in western Nepal: Banke, Baitadi, Kailali, and Surkhet. Banke and Kailali are located in the Terai (lowland) region, whereas Baitadi and Surkhet represent hill areas. These districts were selected because they were areas where agricultural value chain development programs were particularly active and they illustrate a mix of production conditions. Banke and Kailali are easily accessible areas, but they are dominated by cereal production with relatively low productivity. Baitadi and Surkhet are less accessible, with diversified production that is less commercially oriented.

Within each district, settlements were selected where agricultural groups had submitted grant proposals to RISMFP as of 2013, although groups were free to apply to other projects at any point. For every treated settlement, two comparable *comparison* settlements, similar in terms of dominant crops, market proximity, population, and presence of farmer groups, were selected. A listing exercise was conducted in each settlement, from which 15 households were randomly selected for enumeration.

4.2 Data Collection

We rely on three rounds of household-, farmer group or cooperative-, and settlement-level surveys conducted in April 2014 (baseline), July 2018 (midline), and August 2022 (endline). The baseline sample included 204 settlements; however, subsequent rounds focused on areas where agricultural support was implemented, reducing the sample to

162 settlements at midline and 129 at endline. Households were dropped if the overall locality never received support, but panel attrition was minimal: 6% at midline and 5% at endline. Replacements were drawn from the same settlement when needed, but only original panel households are used in the analysis.

The household surveys collected information on demographics, landholding, input use, crop and livestock production, labor allocation, group membership, and marketing behavior. The final panel consists of 1,521 primarily farming households. On average, farm sizes were small, at around 0.68 hectares of land at baseline, and the area owned by households directly was even lower, at 0.51 hectares at baseline. At baseline, 16% of households were engaged in sharecropping, but this share dropped to 12% at endline. Most households cultivated paddy (43%), wheat (35%), and maize (12%) at baseline (Table 1).

Table 1: Summary Statistics by Round

	(1)	(2)	(3)
	2014	2018	2022
	mean	mean	mean
Farm area (hectares)	0.68	0.57	0.59
Farm area owned (hectares)	0.51	0.46	0.45
Sharecropper (0–1)	0.16	0.10	0.12
Cultivates rice (0–1)	0.43	0.35	0.34
Cultivates wheat (0–1)	0.35	0.34	0.31
Cultivates maize (0–1)	0.12	0.13	0.12
Cultivates vegetables (0–1)	0.03	0.03	0.04
Any crop sales (0–1)	0.53	0.54	0.53
Value of crop sales (NRs)	30,204	40,947	49,439
Ag. income as share of total (0–1)	0.47	0.37	0.34
Has nonfarm business (0–1)	0.23	0.20	0.23
Has wage job (0–1)	0.34	0.45	0.45
Has remittance income (0–1)	0.37	0.33	0.37
Observations	1,521	1,521	1,521

Ag. = agricultural, NRs = Nepali rupees.

Note: Restricted to 1,521 panel households that were surveyed in all rounds and were cultivating land.

Crop sale amount is conditional on selling any crops. 2014 = baseline, 2018 = midline, 2022 = endline.

Source: Authors' calculations using household surveys 2014–2022.

Only 3% of households cultivated vegetables at baseline, excluding those cultivating on small kitchen garden plots for the household's own consumption. At baseline, 53% reported selling crops in the market, with average annual crop sale income of around NRs30,204 (\$309).³ These small numbers understate the contribution of agriculture to total household income. After accounting for livestock sales, other production (such as beekeeping or agricultural byproduct sales), and the value of self-consumed crops,

³ Conversion carried out using official exchange rates from the World Bank's data portal for the year 2014. \$1 = NRs97.55.

agriculture accounts for 47% of total household income at baseline. This share drops to 34% by endline, as more households engage in nonfarm wage employment, which went up from 34% at baseline to 45% at endline. While 35% of households had some remittance income at baseline, this figure slightly increases to 37% at endline, which underscores the continued importance of remittances to total household income in Nepal post COVID-19.

4.3 Interventions Received

Table 2 shows the uptake of support across three survey rounds among the 1,521 panel households that were interviewed in all rounds. By the 2018 midline, 44% of these households had received some form of support in the last 4 years. The most common interventions were agricultural inputs (39%), followed by production training (14%) and productive assets (10%). The majority of households (86%) that received training also received inputs between 2014 and 2018. Provision of fixed assets alongside training was rarer, with one in three trained households receiving fixed assets by 2018 and only 46% of trained households received fixed assets by 2022.

Table 2: Treatment Take-up by Round

	(1)	(2)	(3)
	2014	2018	2022
No support	1,011	849	925
Any support in past 4 years	510	672	596
Fertilizer and seeds	252	593	467
Training	114	209	86
Fixed assets, irrigation, machinery	0	159	108
Any credit support	241	134	163
Marketing, storage, transport	17	20	7
High value crop production support	180	512	213
Vegetable production support	80	273	136
Seed production support	121	236	58
Fruit and cash crop production support	28	36	44
Cereal (excluding seed) production support	0	33	30
Livestock support	6	32	27
Observations	1,521	1,521	1,521

Note: Restricted to 1,521 panel households that were surveyed in all rounds and were cultivating land. High value crop production includes fruit, vegetable, cash crops, and cereal seed production support. 2014 = baseline, 2018 = midline, 2022 = endline.

Source: Authors' calculations using household surveys 2014–2022.

Most programs offered a combination of group-based training and input provision. The most common topics of training were crop production, new varieties, and pest control (Table 3). Very few households received training on livestock rearing and marketing of their agricultural products.

Table 3: Farmer Group Training Topics by Round

	(1)	(2)
	2018	2022
	mean	mean
Crop production	0.07	0.09
New seed variety	0.04	0.04
Input use	0.02	0.01
Pest control	0.01	0.08
Integrated crop management	0.01	0.01
New livestock	0.03	0.03
New crop	0.02	0.02
Other new products	0.01	0.01
Other topics	0.02	0.03
Postharvest/storage	0.00	0.03
Agronomy/pest control	0.14	0.06
Postharvest/processing	0.07	0.03
Livestock	0.01	0.01
Marketing	0.02	0.00
Observations	1,521	1,521

Note: This table shows the share of households that received training on each topic. If a household did not receive any training or is not part of a farmer group, it is set to 0. The top half of the table shows values reported in the agricultural farmer group and cooperative survey; values on the bottom are those reported by individual households that attended the trainings. 2018 = midline, 2022 = endline.
Source: Authors' calculations using household and group surveys 2018–2022.

Most farmers who are members of an agricultural group received fertilizer (60% up to 2018 and 52% up to 2022) from the group (Table 4). A similar share of farmers who are group members received seeds (62%) up to 2018 but this share dropped after that to only 23%. This suggests the new projects that supported farmers past 2018 focused more on fertilizer provision, rather than providing new seed varieties and training farmers to adopt new technologies. About 11% of group member farmers reported receiving power tillers and 10% received irrigation equipment between 2014 and 2018. Only 4% of

farmers reported receiving plastic tunnels in between 2014 and 2018, suggesting that most vegetables were not cultivated in greenhouses or plastic tunnels. These low rates of productive asset transfers suggest that we will not see statistically significant increases in farm total factor productivity.

Table 4: Farmer Received Inputs from Group by Round

	(1)	(2)
	2018	2022
	mean	mean
Fertilizer	0.60	0.52
Seed	0.62	0.23
Power tillers	0.11	0.06
Irrigation equipment	0.10	0.06
Plastic tunnel	0.04	0.04
Storage bins	0.01	0.00
Other	0.12	0.05
Observations	832	832

Note: This table is restricted to households that are members of either a farmer group or a cooperative in each survey round. This table shows the share of households that received inputs or assets from farmer groups and cooperatives. If a household did not receive any inputs or assets then the value is set to 0. If a household is not a member of a farmer group or cooperative then the value of outcome is set to missing. 2018 = midline, 2022 = endline.

Source: Authors' calculations using household surveys 2018–2022.

5 METHODOLOGY

5.1 Estimation Strategy

The focus of the research is on the effects of agricultural support channeled via agricultural groups and cooperatives, the persistence of those effects, and how those effects interact with COVID-19. To carry out our study, we examine three broad outcome categories and five outcomes, which are derived from the theory of change outlined earlier:

1. **Agricultural practices:** More commercial-oriented production is expected to increase overall variable *input costs* as production becomes more intensified.

2. **Agricultural practices:** Improved use of inputs should lead to greater *total factor productivity*, measured as the residual from a production Cobb-Douglas function.
3. **Agricultural practices:** Greater productivity should drive increases in *production value* for crop outputs.
4. **Farm revenues:** Higher production value in the context of commercialization goals should drive increased *total revenue from crop sales*.
5. **Household-level outcomes:** Increased crop sales are expected to increase *total income per capita*, measured without remittances.

We estimate the following household fixed effects model using data from three survey rounds:

$$\begin{aligned}
y_{it} = & \beta_1 Treatment2018_{it} \\
& + \beta_2 Treatment2022_{it} \\
& + \beta_3 Treatment2018_{it-1} \\
& + \beta_4 M_{it} \\
& + \beta_5 M_{it} \times Treatment2022_{it} \\
& + \beta_6 M_{it} \times Treatment2018_{it-1} \\
& + X'_i \alpha + \delta_i + \nu_t + \varepsilon_{it}
\end{aligned} \tag{1}$$

In this specification, y_{it} represents household-level outcomes such as crop cultivation costs, harvested crop values, crop sales, or total income for household i in period t . The variable $Treatment2018_{it}$ indicates whether the household received support between 2014 and first half of 2018. $Treatment2022_{it}$ indicates whether the household received support between the second half of 2018 and 2022 and $_{it-1}$ denotes treatment in the previous round. The variable M_{it} captures market-level exposure to COVID-19 disruptions, which takes value of 1 if the main market to sell crops had restricted operations for at least 1 month between April 2021 and August 2022, based on World Food Program's (WFP) market price reports.⁴(Figure A1) Overall 28% of our study

⁴ WFP's Vulnerability Analysis and Mapping unit provides monthly food prices for all major markets in Nepal. VAM provides prices for 15 to 21 food items in each market. We classified the market as having restricted operations if in any month between April 2021 and August 2022 the number of food items sold in the

sample were serviced by markets that had operations restricted in the second round of COVID-19 movement restrictions in 2021. The share of households supported between 2014 and first half of 2018 that were serviced by these markets is 31%, and the share for the households supported between second half of 2018 and 2022 is 35%. The interaction terms allow us to estimate whether treatment effects vary by local pandemic-related disruptions.

We include household fixed effects δ_i to control for time-invariant unobserved heterogeneity, and survey round fixed effects ν_t to absorb aggregate time shocks. The vector X_i' includes household-level time-invariant controls, which include walking distance to market and average precipitation by season. Standard errors are clustered at the ward level. Finally, the total effect of $\text{Treatment}_{2018_{it}}$ on the COVID-19 affected households is given by the sum of β_3 and β_6 . The total effect of $\text{Treatment}_{2022_{it}}$ on the COVID-19 affected households is given by the sum of β_2 and β_5 .

Some households had received interventions in the 2014 baseline survey round. However, because there are no pretreatment observations for these households, it is not possible to estimate these effects with much confidence, and inclusion of 2014 treatment coefficients has little bearing on the results presented. Results including 2014 treatment coefficients are available upon request from the authors.

5.2 Addressing Selection into Treatment

Farmers and farmer groups generally self-select to try to obtain support from public sector programs. This means those who obtain support are likely to differ from those who do not. Because participation in agricultural groups and receipt of support were not randomly assigned, there are likely to be baseline differences in characteristics such as agricultural skills, market access, or information that may confound comparisons. To mitigate this, we adopt two complementary approaches: controlling for two-way fixed effects and inverse probability weighting.

market was 4 items short of what each market usually reports. This market activity dataset was merged with household data using GPS coordinates.

Analyses are all performed using two-way fixed effects models that control for common time trends and baseline time-invariant characteristics with time-invariant effects. These models are similar in principle to difference-in-differences analysis. Furthermore, analysis of support is restricted to households that do not change group membership status.

To further address potential selection bias from time-variant effects of differences in baseline characteristics, all regressions are weighted by the inverse of the estimated propensity scores for treatment assignment over time. These weights are calculated using a multinomial logit model that includes both village- and household-level covariates. At the village level, we include the presence of infrastructure projects in the past 5 years—such as irrigation systems, roads, electricity lines, and agricultural collection centers—that may affect program targeting. At the household level, we control for pre-treatment characteristics including crop value, proximity to cooperative offices, road access, self-reported poverty status, landholdings, sharecropped or irrigated land, cropping intensity, and various sources of household income (from remittances, nonfarm work, livestock, and business). We also control for asset ownership, access to electricity, use of financial services, demographic characteristics of household head, and indicators of economic activity.

5.3 Dealing with Zero-Inflated Outcomes

Several of our key outcomes, such as crop and livestock sales, contain a large number of zero values. This is common in agricultural settings where not all households participate in markets every year, and where some production inputs are subsidized or home-produced. While crop value and total income exhibit more continuous distributions, outcomes like crop costs and sales are highly skewed and zero-inflated.

While log and inverse hyperbolic sine (IHS) transformations are often used to normalize skewed distributions, recent studies caution against their use when a large share of the data is zero. In particular, Mullahy and Norton (2024) shows that, in the presence of many zeros, transformed outcome models can yield estimates that vary substantially depending on transformation parameters and that are difficult to interpret. Similarly, Chen and Roth (2023) emphasize that effect estimates from transformed

outcomes with many zeros should not be interpreted as elasticities or percentage changes.

To address these concerns, we estimate models for crop costs, crop sales, and livestock sales using Poisson regressions, which accommodate zero-inflated non-negative outcomes without requiring arbitrary transformations. For crop value and total income, where the distributions are closer to continuous and approximately normal, we use ordinary least squares regression.

5.4 Unconditional Quantile Estimation

The previous analyses are all at the mean. To provide a more complete picture of the effects of providing agricultural support, we use unconditional quantile regression via a recentered influence function (RIF) analysis. This approach allows us to investigate whether the treatment effect was more pronounced for farmers at the top or the bottom of the distribution of the outcome variable. The influence function assesses the effect of removing or adding an observation on the value of an outcome statistic. When the statistic is added to the function, it becomes a RIF, defined as:

$$RIF(Y; q_\tau, F_Y) = q_\tau + \frac{\tau - \mathbf{1}_{\{Y \leq q_\tau\}}}{f_Y(q_\tau)} \quad (2)$$

where Y is the outcome variable and q_τ is the value of the outcome variable at quantile τ . F_Y is the cumulative distribution function of Y . $f_Y(q_\tau)$ is the density of Y at quantile τ . $\mathbf{1}_{\{Y \leq q_\tau\}}$ identifies whether outcome value Y is below q_τ .

The generalized unconditional quantile regression approach developed by Firpo et al. (2009) replaces the raw values of the dependent variable in an ordinary least squares regression with the RIF, which is regressed on the covariates of the model. The RIF can be specified at specific quantiles to enable estimates at different points in the distribution.

We estimate separate RIF regressions for the 10th through 90th percentiles (in steps of 10) of two outcomes: crop value and per capita total income. These regressions include the same controls as in our main specification and account for household and survey round fixed effects. Standard errors are clustered at the group level.

5.5 Limitations

The methods applied can generally control for observable differences at baseline between households that received and did not receive support, as well as time-invariant variables with time invariant effects. However, the methods cannot control for time-variant unobserved variables or unobserved variables with time variant effects. Such confounders can only be controlled by use of an appropriate instrumental variable, a running variable with a discontinuity determining eligibility, or in the presence of randomized assignment. For the studied interventions from multiple programs, none of these is applicable. For these reasons, while the estimates seek to eliminate as much bias as possible, some possible sources cannot be fully eliminated. In addition, the methods cannot identify the effects of support provided more generally to the agricultural sector in Nepal, such as tax exemptions for the import of agricultural machinery, as there is no clear variation to serve as the basis for identification. It may also be noted that the variable characterizing COVID-19 market disruptions is an imperfect external proxy, as no highly granular data on disruptions are available, and self-reporting is affected by endogeneity (those who are more commercialized may be more aware of market disruptions). The one year period of recall of agriculture and livelihood activities in 2022 also only partially overlaps the period of COVID-19 disruptions, so outcomes in the most adversely impacted period are not included.

6 RESULTS

This section presents the main empirical findings on the impacts of agricultural support. We begin by confirming that the treatment and comparison groups are well balanced on key baseline characteristics, after applying inverse probability weights based on multinomial logit models. We then estimate the average effects of receiving any form of support and proceed to disaggregate results by type of intervention. Finally, we examine the distributional effects of receiving support. For all results, table exhibits show the raw coefficients, whereas the text presents percentage approximation based on $100 * (\exp(\text{coefficient}) - 1)$.

6.1 Balance After Weighting

The weighting technique applied was able to achieve balance on observable characteristics. Table A1 presents the comparison for households that received support between 2014 and first half of 2018 versus those that did not receive support in the same time period, and the data used is from the 2014 round. The table excludes households that left support from 2014 to 2018 or from 2018 to 2022. Out of 1011 households, 348 started to receive program support between 2014 and first half of 2018, and 663 did not (Table A1). All comparisons are weighted using multinomial logit propensity scores, reflecting the probability of treatment switching. Table A2 presents the baseline difference between households that started to receive support between the second half of 2018 and 2022 and those that did not receive support in the same period under the same weighting approach.

Both supported and unsupported groups in both comparisons are broadly similar across a wide range of demographic and socioeconomic indicators. Household size, education, and age are closely aligned. For example, for households which started to receive support between 2014 and first half of 2018, the average household size is 7.03 in the comparison group and 6.68 in the treated group, years of education differ by only 0.16 years, and the probability of renting out land is the similarly low for both groups. Most other agricultural indicators, such as asset ownership and service access, also show minimal differences. Households that started support between 2014 and 2018 and comparison households report similar rates of machinery ownership, business activity, access to grid electricity, and bank account usage. Agricultural production characteristics, such as land ownership, rice intensity, share of irrigated land, and walking distance to plots, are well balanced.

6.2 Effects of Agricultural Support

6.2.1 Overall Effect of Any Support

We begin by estimating the average effect of receiving any form of agricultural support within the past 4 years, as reported in Table 5. The treatment indicator equals 1 if a

household received at least one of the following forms of support in the 4 years preceding the survey: input support (fertilizer and seeds), agricultural training, fixed asset subsidies, or credit.

Receiving support had large and significant positive impacts on crop costs (+34%), crop values (+27%), and crop sales (+28%) for support up to 2018. These improvements to crop outcomes did not translate into statistically significant increases in per capita total income. The agricultural support provided between second half of 2018 and 2022 in areas unaffected by COVID-19 was successful in increasing crop cultivation, with total factor productivity (TFP) increasing 30% and value of cultivated crops increasing 36% in 2022. These increases did not translate into statistically significant increased crop sales in 2022, but income does show a 27% response. The areas affected by COVID-19 market restrictions saw large and significant decreases in crop value (-41%) and a large 66% decrease in crop sales. The support provided between 2018 and 2022 offset these losses, and contributed much larger gains among the COVID-19 market closure areas than elsewhere, with effects that more or less canceled the COVID-19 coefficients, with the exception of sales, for which about half of the loss was mitigated. Despite net sales reductions, these households still had positive income effects from post-2018 support in COVID-19 areas.

The results indicate how treatment up to 2018 also enhanced resilience to COVID-19 shocks. Households that were supported between 2014 and first half of 2018 but did not receive support between second half of 2018 and 2022 still saw positive gains from the residual impact of prior support in the face of COVID-19 disruptions. These households saw a 45% increase in crop values, and a 77% increase in crop sales compared to households that did not receive support. This suggests that households supported between 2014 and 2018 were better able to withstand the market disruptions caused by COVID-19 restrictions.

Table 5: Effect of Any Support in Past 4 Years

	Crop costs (log)	TFP (log)	Crop values (log)	Crop sales (log)	Income pc (log)
	(1)	(2)	(3)	(4)	(5)
Treatment 2018	0.29** (0.14)	0.08 (0.06)	0.24*** (0.06)	0.25** (0.13)	0.01 (0.09)
Treatment 2022	0.29 (0.26)	0.26** (0.12)	0.31** (0.13)	0.18 (0.21)	0.24** (0.11)
Lag treatment 2018	0.05 (0.26)	0.06 (0.11)	-0.03 (0.09)	-0.23 (0.27)	-0.06 (0.11)
COVID-19 affected	-0.47 (0.32)	0.06 (0.16)	-0.53*** (0.02)	-1.08*** (0.33)	-0.11 (0.13)
COVID-19 affected x treatment 2022	0.33 (0.36)	-0.11 (0.19)	0.14 (0.20)	0.35 (0.29)	0.11 (0.20)
COVID-19 affected x lag treatment 2018	0.21 (0.45)	-0.03 (0.19)	0.41** (0.19)	0.80** (0.37)	0.05 (0.16)
Treatment 2018 on COVID-19 affected	0.26	0.04	0.37**	0.57**	-0.01
Treatment 2022 on COVID-19 affected	0.62**	0.15	0.45***	0.53**	0.35**
Baseline comparison mean	8.55	-0.03	10.24	4.37	9.30
Observations	4,493	4,561	4,563	3,486	4,563
Household and time fixed effects	Yes	Yes	Yes	Yes	Yes
Method	Poisson	OLS	OLS	Poisson	Poisson

COVID-19 = coronavirus disease, OLS = ordinary least squares, pc = per capita, TFP = total factor productivity.

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors in parentheses clustered at the ward level. All estimations are weighted with inverse probability weights calculated by estimating multinomial logit of treatment switch on the baseline characteristics. *Treatment 2018* refers to households which received agricultural support via groups between 2014 and first half of 2018. *Treatment 2022* refers to households which received agricultural support via groups between the second half of 2018 and 2022. *Treatment 2018 on COVID-19 affected* is the linear combination of the point estimates on *Lag treatment 2018* and *COVID-19 affected x lag treatment 2018*. *Treatment 2022 on COVID-19 affected* is the linear combination of the point estimates on *Treatment 2022* and *COVID-19 affected x treatment 2022*.

Source: Authors' calculations using household surveys 2014–2022.

6.2.2 Effects by Type of Support

To unpack the aggregate effects, we disaggregate the treatment by type of support received— higher value production support, input subsidies, agricultural training, asset subsidies, and credit support, using Tables 6 through 10. This allows us to identify which components of the overall program were most effective. However, it should be noted that most households received combinations of support, so the effects estimated are for support that includes the assessed type, but that is often in combination with other support. This means the effects should not be interpreted as being from the type of

support alone, but rather as being from support that included the assessed element. For this reason, effects may be larger than typically estimated for the element in isolation.

Effect of Support To High Value Crop Production. In Table 6 we restrict to support which focused on production of high value crops, such as vegetables, fruit, cash crops and cereal seed production. These higher value crops were targeted specifically by a number of the programs with a commercialization orientation. Cereal seeds are self-multiplied foundation seeds that were distributed by the government's Nepal Agricultural Research Council (NARC). The foundation seeds are not for household's own consumption, but rather purchased by other farmers to plant their next year's crops. Households which received agricultural support with a focus on high value crops saw higher TFP from support in 2018 (+23%) and support in 2022 (+58%) in the absence of COVID-19 disruptions. The value of produced crops also increased in 2018 (+33%), and in 2022 (+57%) for households not affected by COVID-19 restrictions. In COVID-19 affected areas, post-2018 support not only increased crop values by 127%, but also increased sales by 58% and income by 49%. Support for high value production had large effects in mitigating the effects of COVID-19 closure, but the effects have limited persistence, as those mitigating effects only occurred for post-2018 support.

Table 6: Effect of High Value Support

	Crop costs (log)	TFP (log)	Crop values (log)	Crop sales (log)	Income pc (log)
	(1)	(2)	(3)	(4)	(5)
Treatment 2018	-0.17 (0.25)	0.21** (0.10)	0.29*** (0.11)	0.17 (0.24)	0.07 (0.12)
Treatment 2022	-0.51 (0.32)	0.46** (0.18)	0.45*** (0.16)	-0.21 (0.29)	0.15 (0.15)
Lag treatment 2018	-0.52* (0.29)	0.13 (0.19)	0.08 (0.12)	-0.34 (0.30)	-0.08 (0.20)
COVID-19 affected	-0.29 (0.35)	0.18 (0.31)	-0.25* (0.13)	-1.03*** (0.26)	-0.08 (0.20)
COVID-19 affected x treatment 2022	1.05* (0.61)	-0.11 (0.32)	0.37 (0.39)	0.67** (0.32)	0.24 (0.24)
COVID-19 affected x lag treatment 2018	0.08 (0.58)	-0.22 (0.33)	-0.15 (0.21)	0.40 (0.30)	-0.02 (0.28)
Treatment 2018 on the COVID-19 affected	-0.44	-0.09	-0.08	0.07	-0.10
Treatment 2022 on the COVID-19 affected	0.54	0.34	0.82**	0.46**	0.40*
Baseline comparison mean	8.55	-0.03	10.24	4.37	9.30
Observations	3,418	3,536	3,537	2,568	3,537
Household and time fixed effects	Yes	Yes	Yes	Yes	Yes
Method	Poisson	OLS	OLS	Poisson	Poisson

COVID-19 = coronavirus disease, OLS = ordinary least squares, pc = per capita, TFP = total factor productivity.

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors in parentheses clustered at the ward level. All estimations are weighted with inverse probability weights calculated by estimating multinomial logit of treatment switch on the baseline characteristics. *Treatment 2018* refers to households which received agricultural support via groups between 2014 and first half of 2018. *Treatment 2022* refers to households which received agricultural support via groups between the second half of 2018 and 2022. *Treatment 2018 on COVID-19 affected* is the linear combination of the point estimates on *Lag treatment 2018* and *COVID-19 affected x lag treatment 2018*. *Treatment 2022 on COVID-19 affected* is the linear combination of the point estimates on *Treatment 2022* and *COVID-19 affected x treatment 2022*.

Source: Authors' calculations using household surveys 2014–2022.

Effect of Support That Included Input Subsidies. Table 7 presents the estimated effects of agricultural support via groups that includes a fertilizer and seed subsidies component. Provision of these inputs had a short and positive impact on crop cultivation, with a 35% increase in crops sales in 2018. The effects on crop cultivation in 2022 in areas unaffected by COVID-19 disruptions were more pronounced, with a 31% increase in TFP and a 34% increase in the value of all crops cultivated, but these increases did not translate into higher crop sales in 2022. Households without subsidies and in COVID-affected areas saw large decreases in crop values and crop sales, whereas post-2018 subsidies had significant effects that equally offset or exceeded COVID-19 losses on all outcomes except crop sales. Households that received inputs between 2014 and 2018, but did not receive them

after 2018, had a significant COVID-19 offsetting effect only on crop sales, which suggests effects were only somewhat persistent in improving resilience.

Table 7: Effect of Support That Included Input Subsidies

	Crop costs (log)	TFP (log)	Crop values (log)	Crop sales (log)	Income pc (log)
	(1)	(2)	(3)	(4)	(5)
Treatment 2018	0.17 (0.15)	-0.01 (0.09)	0.17 (0.12)	0.30** (0.14)	-0.06 (0.08)
Treatment 2022	0.48 (0.31)	0.27** (0.13)	0.29** (0.13)	0.14 (0.29)	0.13 (0.11)
Lag treatment 2018	0.06 (0.26)	0.07 (0.17)	0.04 (0.13)	-0.18 (0.35)	0.10 (0.26)
COVID-19 affected	-0.32 (0.24)	0.10 (0.22)	-0.42*** (0.16)	-1.25*** (0.40)	-0.10 (0.16)
COVID-19 affected x treatment 2022	0.21 (0.40)	-0.07 (0.21)	0.11 (0.22)	0.49 (0.38)	0.15 (0.19)
COVID-19 affected x lag treatment 2018	0.24 (0.38)	-0.16 (0.25)	0.13 (0.29)	0.71 (0.44)	-0.21 (0.29)
Treatment 2018 on COVID-19 affected	0.30	-0.09	0.17	0.54*	-0.12
Treatment 2022 on COVID-19 affected	0.69***	0.19	0.40**	0.63**	0.28*
Baseline comparison mean	8.55	-0.03	10.24	4.37	9.30
Observations	3,919	4,044	4,046	3,022	4,046
Household and time fixed effects	Yes	Yes	Yes	Yes	Yes
Method	Poisson	OLS	OLS	Poisson	Poisson

COVID-19 = coronavirus disease, OLS = ordinary least squares, pc = per capita, TFP = total factor productivity.

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses clustered at the ward level. All estimations are weighted with inverse probability weights calculated by estimating multinomial logit of treatment switch on the baseline characteristics. *Treatment 2018* refers to households which received agricultural support via groups between 2014 and first half of 2018. *Treatment 2022* refers to households which received agricultural support via groups between the second half of 2018 and 2022. *Treatment 2018 on COVID-19 affected* is the linear combination of the point estimates on *Lag treatment 2018* and *COVID-19 affected x lag treatment 2018*. *Treatment 2022 on COVID-19 affected* is the linear combination of the point estimates on *Treatment 2022* and *COVID-19 affected x treatment 2022*.

Source: Authors' calculations using household surveys 2014–2022.

Effect of Support That Included Training. Table 8 shows the estimated effects of agricultural support via groups that includes a training component. When comparing the impacts of support including training and input subsidies, training has larger and more consistent effects on crop production costs and crop sales between 2014 and 2018. Households that received training up to 2018 saw a 28% increase in TFP, a 60% increase in crop value, and an 86% increase in sales. Most of these effects are similar for treatment between 2018 and 2022 in areas unaffected by COVID-19 disruptions.

Households that did not receive training have negative COVID-19 effects on crop production and sales, similar to previous tables. Yet the training received between 2018-2022 had positive effects on COVID-affected households that exceeded all the negative consequences of COVID-19 disruptions. Moreover, this enabled significant and substantial income gains. The coefficients for training between 2014 and 2018 suggest substantial residual effects in COVID-19 affected areas on TFP, crop value, and sales, but they are statistically insignificant because there are few training recipients who did not continue training after 2018 in COVID-19 affected areas.

Table 8: Effect of Support That Included Training

	Crop costs (log)	TFP (log)	Crop values (log)	Crop sales (log)	Income pc (log)
	(1)	(2)	(3)	(4)	(5)
Treatment 2018	0.88*** (0.31)	0.25** (0.12)	0.47*** (0.13)	0.62*** (0.21)	0.08 (0.18)
Treatment 2022	0.49 (0.59)	0.30 (0.28)	0.46** (0.22)	0.78*** (0.29)	0.17 (0.18)
Lag treatment 2018	0.40* (0.23)	-0.34* (0.20)	-0.30** (0.15)	-1.36** (0.65)	-0.28* (0.16)
COVID-19 affected	0.76 (0.62)	0.01 (0.17)	-0.37** (0.16)	-0.20 (0.36)	-0.30** (0.12)
COVID-19 affected x treatment 2022	-0.56 (0.89)	0.23 (0.33)	0.58* (0.32)	0.01 (0.47)	0.35 (0.22)
COVID-19 affected x lag treatment 2018	-0.15 (0.91)	0.89** (0.39)	1.05 (0.70)	1.93** (0.81)	0.19 (0.21)
Treatment 2018 on COVID-19 affected	0.25	0.55	0.75	0.57	-0.09
Treatment 2022 on COVID-19 affected	-0.08	0.53***	1.04***	0.79**	0.52***
Baseline comparison mean	8.55	-0.03	10.24	4.37	9.30
Observations	2,798	2,889	2,890	2,028	2,890
Household and time fixed effects	Yes	Yes	Yes	Yes	Yes
Method	Poisson	OLS	OLS	Poisson	Poisson

COVID-19 = coronavirus disease, OLS = ordinary least squares, pc = per capita, TFP = total factor productivity.

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors in parentheses clustered at the ward level. All estimations are weighted with inverse probability weights calculated by estimating multinomial logit of treatment switch on the baseline characteristics. *Treatment 2018* refers to households which received agricultural support via groups between 2014 and first half of 2018. *Treatment 2022* refers to households which received agricultural support via groups between the second half of 2018 and 2022. *Treatment 2018 on COVID-19 affected* is the linear combination of the point estimates on *Lag treatment 2018* and *COVID-19 affected x lag treatment 2018*. *Treatment 2022 on COVID-19 affected* is the linear combination of the point estimates on *Treatment 2022* and *COVID-19 affected x treatment 2022*.

Source: Authors' calculations using household surveys 2014–2022.

Effect of Support That Included Productive Asset Provision. Table 9 presents the estimated effects of agricultural support via groups that includes productive asset

provision, which are mostly isolated to households that received fixed assets up to 2018. Provision of fixed assets was successful at increasing crop sales in 2018 by 55%. We do not observe impacts of asset support in 2022 in areas unaffected by COVID-19, but there are significant impacts on crop values (55%) and sales (90%) in COVID-19 affected areas. Receiving fixed assets between 2014-2018 also had residual impacts in 2022 for households in COVID-affected areas with increased crop value (+43%) and per capita income (+51%). This suggests that households that received assets between 2014-2018 were better prepared to endure COVID-related disruptions to the agricultural value chain.

Table 9: Effect of Support That Included Productive Asset Provision

	Crop costs (log)	TFP (log)	Crop values (log)	Crop sales (log)	Income pc (log)
	(1)	(2)	(3)	(4)	(5)
Treatment 2018	0.01 (0.32)	0.36 (0.22)	0.15 (0.15)	0.44* (0.24)	0.17 (0.19)
Treatment 2022	0.01 (0.37)	-0.13 (0.27)	0.04 (0.24)	-0.28 (0.49)	-0.09 (0.26)
Lag treatment 2018	-0.14 (0.26)	-0.12 (0.23)	-0.08 (0.15)	-0.45 (0.55)	-0.53* (0.32)
COVID-19 affected	-0.19 (0.15)	-0.17 (0.15)	-0.39*** (0.11)	-1.19** (0.50)	-0.27 (0.19)
COVID-19 affected x treatment 2022	0.54 (0.41)	0.18 (0.42)	0.40* (0.24)	0.92* (0.54)	0.14 (0.31)
COVID-19 affected x lag treatment 2018	-0.77** (0.30)	0.10 (0.23)	0.45** (0.21)	0.75 (0.58)	0.94** (0.37)
Treatment 2018 on COVID-19 affected	-0.91***	-0.03	0.36**	0.30	0.41*
Treatment 2022 on COVID-19 affected	0.54*	0.06	0.44**	0.64**	0.05
Baseline comparison mean	8.55	-0.03	10.24	4.37	9.30
Observations	2,640	2,729	2,730	1,916	2,730
Household and time fixed effects	Yes	Yes	Yes	Yes	Yes
Method	Poisson	OLS	OLS	Poisson	Poisson

COVID-19 = coronavirus disease, OLS = ordinary least squares, pc = per capita, TFP = total factor productivity.

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors in parentheses clustered at the ward level. All estimations are weighted with inverse probability weights calculated by estimating multinomial logit of treatment switch on the baseline characteristics. *Treatment 2018* refers to households which received agricultural support via groups between 2014 and first half of 2018. *Treatment 2022* refers to households which received agricultural support via groups between the second half of 2018 and 2022. *Treatment 2018 on COVID-19 affected* is the linear combination of the point estimates on *Lag treatment 2018* and *COVID-19 affected x lag treatment 2018*. *Treatment 2022 on COVID-19 affected* is the linear combination of the point estimates on *Treatment 2022* and *COVID-19 affected x treatment 2022*.

Source: Authors' calculations using household surveys 2014–2022.

Effect of Support That Included Credit Provision. Table 10 shows the estimated effects of agricultural support via groups that includes credit provision. This support was

often provided in the form of low-interest loans taken from agricultural cooperatives where other members deposited their savings. The purpose of these loans is not always agricultural, with some farmers using these loans to smooth consumption shocks or cover transportation costs to send household members to work abroad. Provision of supporting including credit between 2014–2018 increased 2018 crop values (+54%), and sales (+67%), but did not increase total per capita income. Households that received credit from groups after 2018 in non-COVID-affected areas did not show changes to crop cultivation or sales, although income responded significantly.

Those that received credit in COVID-affected areas after 2018 had effects that canceled out COVID-19 losses to crop value, and sales. In addition, households that benefited from credit between 2014-2018 saw positive residual effects during 2022 in COVID-affected areas that canceled out COVID-19 effects on crop value and sales, so the persistent effect of previous credit was important to resilience.

Table 10: Effect of Support That Included Credit Provision

	Crop costs (log)	TFP (log)	Crop values (log)	Crop sales (log)	Income pc (log)
	(1)	(2)	(3)	(4)	(5)
Treatment 2018	0.10 (0.37)	-0.07 (0.16)	0.43*** (0.12)	0.51** (0.25)	-0.09 (0.16)
Treatment 2022	0.21 (0.38)	0.11 (0.18)	-0.12 (0.17)	0.24 (0.48)	0.36** (0.15)
Lag treatment 2018	-0.42 (0.42)	-0.33* (0.19)	-0.40* (0.20)	-0.83 (0.51)	-0.17 (0.16)
COVID-19 affected	-0.91*** (0.30)	-0.07 (0.15)	-0.43*** (0.16)	-0.76*** (0.28)	-0.08 (0.15)
COVID-19 affected x treatment 2022	0.96 (0.67)	0.24 (0.28)	0.57** (0.29)	0.49 (0.55)	-0.16 (0.31)
COVID-19 affected x lag treatment 2018	1.03** (0.49)	0.53 (0.38)	1.08*** (0.36)	1.57*** (0.54)	0.33 (0.38)
Treatment 2018 on COVID-19 affected	0.61	0.20	0.69**	0.74**	0.16
Treatment 2022 on COVID-19 affected	1.16**	0.34	0.45*	0.72*	0.20
Baseline comparison mean	8.55	-0.03	10.24	4.37	9.30
Observations	3,003	3,070	3,071	2,109	3,071
Household and time fixed effects	Yes	Yes	Yes	Yes	Yes
Method	Poisson	OLS	OLS	Poisson	Poisson

COVID-19 = coronavirus disease, OLS = ordinary least squares, pc = per capita, TFP = total factor productivity.

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors in parentheses clustered at the ward level. All estimations are weighted with inverse probability weights calculated by estimating multinomial logit of treatment switch on the baseline characteristics. *Treatment 2018* refers to households which received agricultural support via groups between 2014 and first half of 2018. *Treatment 2022* refers to households which received agricultural support via groups between the second half of 2018 and 2022. *Treatment 2018 on COVID-19 affected* is the linear combination of the point estimates on *Lag treatment 2018* and *COVID-19 affected x lag treatment 2018*. *Treatment 2022 on COVID-19 affected* is the linear combination of the point estimates on *Treatment 2022* and *COVID-19 affected x treatment 2022*.

Source: Authors' calculations using household surveys 2014–2022.

6.3 Distributional Effects of Support

While average treatment effects tell us whether agricultural support programs were effective on the whole, they can hide important variations in who benefited the most. To explore this, we estimate quantile regressions to examine how the effects vary across the outcome distribution—specifically, whether households at the bottom, middle, or top of the crop value and income distributions experienced different impacts. The key variables of interest indicate whether the household received any support or training during the previous 4 years. In the following, we investigate the distributional effects of any support and training in the previous 4 years.

6.3.1 Crop Value

We begin by examining the distributional impact of receiving any agricultural support in the past 4 years on crop value. Table 11 presents quantile regression estimates of receiving any support on log crop value. The 2014-2018 treatment effects on crop value are statistically significant between the 20th and 90th percentiles. The magnitude of the effect varies across this range, ranging from 19% to 28% (log point increases from 0.17 to 0.25). Effects are not statistically significant at the bottom (10th) decile, indicating weaker associations among the households with lowest production value.

The 2018-2022 treatment effects show a slightly different pattern: they are significant only in the middle of the distribution. Households at the 40th percentile experienced increases of approximately 34% (0.29). These effects decline slightly across the distribution, dropping to 22% (0.20) at the 80th percentile and becoming statistically insignificant at the 90th percentile.

Table 11: Distributional Effect of Any Support in Past 4 Years

	Outcome: crop value (log)								
	10th	20th	30th	40th	50th	60th	70th	80th	90th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment 2018	0.08	0.21*	0.18**	0.22**	0.20**	0.17*	0.23**	0.21**	0.25**
	(0.19)	(0.11)	(0.08)	(0.09)	(0.09)	(0.10)	(0.10)	(0.08)	(0.11)
Treatment 2022	0.52	0.18	0.13	0.29**	0.21**	0.19*	0.22**	0.20*	0.09
	(0.34)	(0.13)	(0.10)	(0.12)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
Baseline comparison mean	9.01	9.45	9.75	10.04	10.26	10.48	10.73	11.10	11.59
Household and time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,563	4,563	4,563	4,563	4,563	4,563	4,563	4,563	4,563

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses clustered at the ward level. All estimations are weighted with inverse probability weights calculated by estimating multinomial logit of treatment switch on the baseline characteristics. *Treatment 2018* refers to households which received agricultural support via groups between 2014 and first half of 2018. *Treatment 2022* refers to households which received agricultural support via groups between the second half of 2018 and 2022.

Source: Authors' calculations using household surveys 2014–2022.

6.3.2 Total Household Income per Capita

We now turn to the distributional effects of receiving agricultural support on per capita total household income, excluding the income from remittances. Table 12 presents the quantile regression estimates for support received between 2014 and 2018, which has significant impacts at the bottom of the distribution, between the 10th and 20th percentiles. The coefficient of support decreases from 63% at the 10th quantile to 34% at the 20th quantile. Highest-income households mostly draw income from nonfarm business, wage income, and remittances. At endline, support received between 2018 and 2022 improved per capita total household incomes for the bottom 60% of the distribution. The coefficient of support drops from 82% at the 10th percentile to 30% at the 60th percentile. Overall effects on income remained progressive across both periods.

Table 12: Distributional Effect of Any Support in Past 4 Years

	Outcome: income pc (log)								
	10th	20th	30th	40th	50th	60th	70th	80th	90th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment 2018	0.49***	0.29*	0.20	0.20	0.15	0.02	0.02	0.01	0.09
	(0.18)	(0.17)	(0.15)	(0.16)	(0.13)	(0.12)	(0.11)	(0.10)	(0.12)
Treatment 2022	0.60***	0.69***	0.40**	0.22	0.36***	0.26**	0.11	0.12	0.08
	(0.20)	(0.20)	(0.18)	(0.16)	(0.13)	(0.12)	(0.13)	(0.14)	(0.11)
Baseline comparison mean	7.85	8.39	8.90	9.22	9.49	9.78	10.05	10.33	10.64
Household and time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,517	4,517	4,517	4,517	4,517	4,517	4,517	4,517	4,517

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses clustered at the ward level. All estimations are weighted with inverse probability weights calculated by estimating multinomial logit of treatment switch on the baseline characteristics. *Treatment 2018* refers to households which received agricultural support via groups between 2014 and first half of 2018. *Treatment 2022* refers to households which received agricultural support via groups between the second half of 2018 and 2022. Source: Authors' calculations using household surveys 2014–2022.

7 CONCLUSION

This paper evaluates the impact of a multi-dimensional agricultural support programs on farm commercialization and household economic outcomes in Nepal, using three rounds of panel data, collected in 2014, 2018, and 2022. The analysis combines fixed effects

regression with inverse probability weighting to estimate both average treatment effects and distributional impacts, disaggregated by type of support and COVID-19 exposure.

The interventions evaluated consisted of any support received via farmer groups and cooperatives, support with a high value focus, input (fertilizer and seed) subsidies, training, asset (chiefly power tillers and irrigation equipment) support via matching grants, and credit provision. Although we evaluate the specific interventions, most farmers who received the interventions also received additional forms of support, so the effects are not only of the focal intervention, but are of support including the focal intervention. For example, most training recipients also received inputs.

Consistent with our earlier paper (Raitzer and Batmunkh, 2022), we find that any support is effective, but that certain forms of support are more effective than others. In particular, support including training and asset provision have higher and consistent effects, whereas input subsidies mostly have short-term impacts. In addition, we show persistence of impacts from credit.

COVID-related disruptions to transport links, markets, and input provision had negative impacts on farmers in 2022. However, these effects arose mostly in areas that had not received support.

We show that support can both mitigate and improve resilience to a massive market shock as a persistent effect. As a contemporaneous effect, the support provided to farmers between 2018 and 2022 in COVID-affected areas had significant positive impacts on crop productivity, production, and sales that offset losses experienced in COVID-affected areas without support. This is true for high value production support, input provision, asset provision, training, and credit.

Perhaps more importantly, receiving agricultural support received between 2014 and 2018 also improved resilience. Such support preserved productivity that would otherwise be lost and significantly increased crop values and sales in COVID-affected areas in 2022. This effect on crop values is pronounced and significant for asset provision, which had significant positive effects on crop values, and per capita income. Credit and training also have some indications of persistence of effects. In contrast, input subsidies have fewer significant persistent effects from support received between 2014 to 2018.

Both rounds of support generally benefited farmers in the middle of the distribution of crop value. In so doing, they improved the incomes of lower-income households, as these households are more reliant on agricultural income.

The estimated impacts in this evaluation are generally in line with those reported in comparable agricultural interventions in low-income settings, especially when it is considered that most support was multi-dimensional. For example, a systematic review of 21 cooperative programs providing agricultural assets and market support found a moderately strong positive effect on production and yields (0.61 standard deviations), a modest increase in farmer income (0.28 standard deviations), and inconclusive impacts on market access, cultivated area, and poverty reduction (Islam et al., 2015). Similarly, a meta-analysis of 12 input subsidy programs found an average yield increase of 18% (Nguyen et al., 2023). A review of 19 training, innovation, and technology adoption programs reported no statistically significant effect on farmers' income (Stewart et al., 2015).

Several key implications emerge from this study. First, support via farmer groups and cooperatives can be an effective way to improve agricultural production value, productivity, and income, even when provided in the context of a disruption like the COVID-19 pandemic. Second, such support can go beyond having effects in the short run, and can also improve resilience to shocks as a persistent effect. Third, the type of support matters. Training, asset support, and credit lead to larger and more persistent effects compared to other forms of support, such as input subsidies. With more persistent effects, there are lower recurring costs for these interventions to more efficiently drive agricultural development and resilience to shocks, in comparison to subsidies.

Appendix Tables and Figure

Appendix Table A1: Balance Test—Multinomial Logit Weights—Started to Receive Support 2014-2018

Variable	(1) No support Mean/(SE)	(2) Support Mean/(SE)	(1)-(2) Pairwise t-test P-value
Household size (1-30)	7.03 (0.33)	6.68 (0.16)	0.33
Ag. person: education (0-17 years)	2.30 (0.19)	2.46 (0.23)	0.60
Ag. person: age (14-84 years)	44.99 (0.70)	44.76 (0.84)	0.83
Ag. person: female (0-1)	0.54 (0.03)	0.52 (0.03)	0.62
Rented out land (0-1)	0.06 (0.01)	0.05 (0.01)	0.54
Household has ag. machinery (0-1)	0.18 (0.02)	0.17 (0.02)	0.87
Household has business (0-1)	0.25 (0.03)	0.24 (0.03)	0.68
Household has savings account at bank (0-1)	0.58 (0.03)	0.61 (0.03)	0.56
Household has electricity from grid (0-1)	0.53 (0.03)	0.57 (0.03)	0.42
Reports as poor (0-1)	0.26 (0.02)	0.28 (0.03)	0.52
Share of land area owned by household (0-1)	0.81 (0.02)	0.81 (0.02)	0.93
Rice intensity (0-1)	0.21 (0.01)	0.21 (0.01)	0.89
Share farm irrigated (0-1)	0.64 (0.03)	0.65 (0.02)	0.76
Distance to plots (1-6 category)	1.25 (0.02)	1.25 (0.03)	0.83
Household has remittances (0-1)	0.37 (0.03)	0.35 (0.03)	0.59
Household has non-farm wage income (0-1)	0.35 (0.03)	0.31 (0.03)	0.30
Sharecropping (0-1)	0.16 (0.02)	0.16 (0.02)	0.87
Other ag. support (0-1)	0.11 (0.03)	0.11 (0.03)	0.95
Crop value (log)	10.36 (0.07)	10.34 (0.07)	0.87
Cultivable area (log)	0.93 (0.04)	0.90 (0.03)	0.55
Distance: road (log)	2.94 (0.08)	2.90 (0.07)	0.75
Distance: coop office (log)	2.45 (0.04)	2.40 (0.05)	0.47
Income: ag. (log)	10.10 (0.09)	10.12 (0.14)	0.90
Income: non-ag. (log)	7.54 (0.24)	7.06 (0.30)	0.21
F-test of joint significance (F-stat)			0.32
Number of observations	663	348	1011

ag. = agricultural, coop = cooperative, SE = standard error.

Notes: Support column refers to households which started to receive agricultural support between 2014 and first half of 2018. No support column refers to households which did not receive agricultural support via groups in the same time period.

Source: Authors' calculations using household survey 2014.

Appendix Table A2: Balance Test—Multinomial Logit Weights—Started to Receive Support 2018-2022

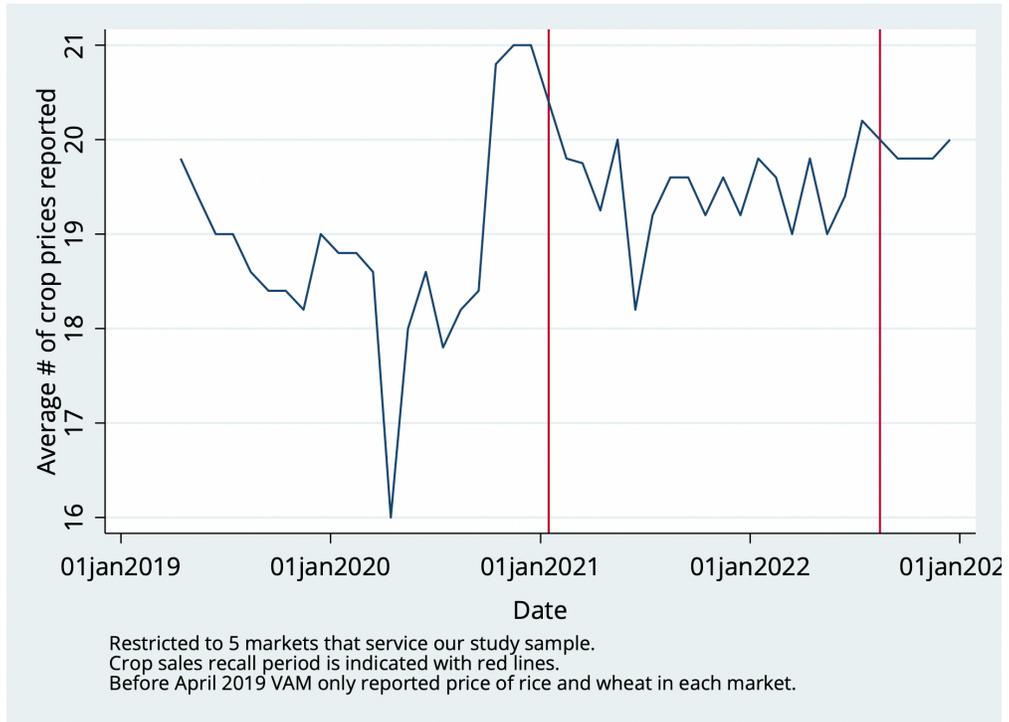
Variable	(1) No support Mean/(SE)	(2) Support Mean/(SE)	(1)-(2) Pairwise t-test P-value
Household size (1-30)	6.91 (0.28)	7.02 (0.32)	0.80
Ag. person: education (0-17 years)	2.40 (0.20)	2.68 (0.34)	0.48
Ag. person: age (14-84 years)	44.99 (0.73)	44.41 (1.11)	0.66
Ag. person: female (0-1)	0.51 (0.03)	0.56 (0.04)	0.36
Rented out land (0-1)	0.06 (0.01)	0.05 (0.02)	0.64
Household has ag. machinery (0-1)	0.18 (0.02)	0.19 (0.04)	0.88
Household has business (0-1)	0.23 (0.02)	0.26 (0.04)	0.58
Household has savings account at bank (0-1)	0.60 (0.03)	0.58 (0.05)	0.71
Household has electricity from grid (0-1)	0.56 (0.03)	0.56 (0.04)	0.97
Reports as poor (0-1)	0.27 (0.02)	0.23 (0.04)	0.32
Share of land area owned by household (0-1)	0.81 (0.02)	0.83 (0.02)	0.41
Rice intensity (0-1)	0.21 (0.01)	0.21 (0.01)	0.60
Share farm irrigated (0-1)	0.66 (0.02)	0.65 (0.04)	0.83
Distance to plots (1-6 category)	1.25 (0.02)	1.24 (0.04)	0.92
Household has remittances (0-1)	0.35 (0.03)	0.39 (0.04)	0.45
Household has non-farm wage income (0-1)	0.34 (0.02)	0.35 (0.04)	0.72
Sharecropping (0-1)	0.16 (0.02)	0.15 (0.03)	0.74
Other ag. support (0-1)	0.10 (0.03)	0.10 (0.03)	0.93
Crop value (log)	10.31 (0.06)	10.43 (0.11)	0.35
Cultivable area (log)	0.91 (0.04)	0.97 (0.07)	0.47
Distance: road (log)	2.87 (0.07)	2.92 (0.12)	0.70
Distance: coop office (log)	2.41 (0.04)	2.41 (0.06)	0.99
Income: ag. (log)	10.02 (0.13)	10.16 (0.21)	0.59
Income: non-ag. (log)	7.18 (0.25)	7.50 (0.46)	0.54
F-test of joint significance (F-stat)			0.43
Number of observations	679	219	898

ag. = agricultural, coop = cooperative, SE = standard error.

Notes: Support column refers to households which started to receive agricultural support between the second half of 2018 and 2022. No support column refers to households which did not receive agricultural support via groups in the same time period.

Source: Authors' calculations using household survey 2014.

Appendix Figure A1: Market Crop Price Reporting



Source: Authors' calculations.

REFERENCES

- Abebaw, D. and Haile, M. G. (2013). The impact of cooperatives on agricultural technology adoption: Empirical evidence from Ethiopia. *Food Policy*, 38:82–91.
- Adhikari, J., Timsina, J., Khadka, S. R., Ghale, Y., and Ojha, H. (2021). COVID-19 impacts on agriculture and food systems in Nepal: Implications for SDGs. *Agricultural Systems*, 186:102990.
- Balew, S., Bulte, E., and Kassie, M. (2025). Short-run subsidies and long-run willingness to pay: Learning and anchoring in an agricultural experiment in Ethiopia. *Am. J. Agric. Econ.*, 107(2):655–669.
- Banerjee, A., Duflo, E., Goldberg, N., Karlan, D., Osei, R., Parienté, W., Shapiro, J., Thuysbaert, B., and Udry, C. (2015). A multifaceted program causes lasting progress for the very poor: Evidence from six countries. *Science*, 348(6236):1260799.
- Banerjee, A., Mookherjee, D., Munshi, K., and Ray, D. (2001). Inequality, control rights, and rent seeking: Sugar cooperatives in Maharashtra. *J. Polit. Econ.*, 109(1):138–190.
- Bekele, N., Obare, G., Mithöfer, D., and Amudavi, D. (2013). The impact of group based training approaches on crop yield, household income and adoption of pest management practices in the smallholder horticultural subsector of Kenya. *Journal of Sustainable Development in Africa*, 15(1):117–140.
- Blair, R., Fortson, K., Lee, J., and Rangarajan, A. (2020). Impacts of a large-scale agricultural training program in Armenia. *Econ. Dev. Cult. Change*, 68(4):1103–1129.
- Boye, M., Ghafoor, A., Wudil, A., Usman, M., Prus, P., Fehér, A., and Sass, R. (2024). Youth engagement in agribusiness: Perception, constraints, and skill training interventions in Africa: A systematic review. *Sustainability*, 16(3):1096.
- Campos, F., Coville, A., Fernandes, A. M., Goldstein, M., and McKenzie, D. (2014). Learning from the experiments that never happened: Lessons from trying to conduct randomized evaluations of matching grant programs in Africa. *Journal of the Japanese and International Economies*, 33:4–24.
- Chen, J. and Roth, J. (2023). Logs with zeros? Some problems and solutions. *Q. J. Econ.*, 139(2):891–936.
- Dar, M. H., de Janvry, A., Emerick, K., Kelley, E. M., and Sadoulet, E. (2022). Casting a wider net: Sharing information beyond social networks. Working paper, Center for Effective Global Action (CEGA).

- Duflo, E., Kremer, M., and Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review*, 101(6):2350–90.
- Emerick, K. and Dar, M. H. (2021). Farmer field days and demonstrator selection for increasing technology adoption. *Review of Economics and Statistics*, 103(4):680–693.
- Firpo, S., Fortin, N. M., and Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica*, 77(3):953–973.
- Fischer, E. and Qaim, M. (2012). Linking smallholders to markets: Determinants and impacts of farmer collective action in Kenya. *World Development*, 40(6):1255–1268.
- Fishman, R., Smith, S. C., Bobić, V., and Sulaiman, M. (2022). Can agricultural extension and input support be discontinued? Evidence from a randomized phaseout in Uganda. *Review of Economics and Statistics*, 104(6):1273–1288.
- Gautam, S., Choudhary, D., and Rahut, D. B. (2022). Behavior of private retailers in a regulated input market: An empirical analysis of the fertilizer subsidy policy in Nepal. *Asian Development Review*, 39(2):175–199.
- Geffersa, A. G. and Islam, M. M. (2024). Beyond subsistence? The role of rural cooperatives in driving smallholder commercialization in Ethiopia. *Agribusiness*.
- Gemessa, S. A. (2022). An alternative approach to measuring the welfare implications of input subsidies: Evidence from Malawi. *J. Agric. Econ.*, 73(1):112–138.
- Government of Nepal, Ministry of Agriculture and Livestock Development (2015). Agriculture Development Strategy (ADS) 2015–2035. Technical report, Singha Durbar, Kathmandu, Nepal. Includes an Action Plan and Roadmap for implementation.
- Gugerty, M. K., Biscaye, P., and Anderson, C. L. (2019). Delivering development? Evidence on self-help groups as development intermediaries in South Asia and Africa. *Dev. Policy Rev.*, 37(1):129–151.
- Hossain, M., Mabiso, A., and Garbero, A. (2022). Matching grants and economic activities among horticultural entrepreneurs: Long-term evidence from Rwanda. *World Development*, 150:105712.
- Iddrisu, A. Y., Ouma, S., and Yaro, J. A. (2022). When agricultural commercialization fails: ‘Re-visiting’ value-chain agriculture and its ruins in Northern Ghana. *Globalizations*, pages 1–21.

- IFAD (2021). *Nepal Country Strategic Opportunities Programme 2021-2026*. International Fund for Agricultural Development (IFAD).
- Islam, S., Mazariago, V., Nagarajan, G., and Zama, L. (2015). Effects of farmer cooperatives on expanding agricultural markets in developing countries: A systematic review. Technical report, United States Department of Agriculture, Washington, DC.
- Jayne, T. S., Mason, N. M., Burke, W. J., and Ariga, J. (2018). Review: Taking stock of Africa's second-generation agricultural input subsidy programs. *Food Policy*, 75:1–14.
- Lampach, N., Van Phu, N., and Nguyen To The (2018). Measuring the effect of agricultural extension on technical efficiency in crop farming: Meta-regression analysis. *SSRN Electron. J.*
- Lopez-Ridaura, S., Sanders, A., Barba-Escoto, L., Wiegel, J., Mayorga-Cortes, M., Gonzalez-Esquivel, C., Lopez-Ramirez, M. A., Escoto-Masis, R. M., Morales-Galindo, E., and García-Barcena, T. S. (2021). Immediate impact of COVID-19 pandemic on farming systems in Central America and Mexico. *Agric. Syst.*, 192(103178):103178.
- Mamun, A. (2024). Impact of farm subsidies on global agricultural productivity. *Agricultural Economics*, 55(2):346–364.
- Maïga, W. H. E., Porgo, M., Zohonogo, P., Amegnaglo, C. J., Coulibaly, D. A., Flynn, J., Seogo, W., Traoré, S., Kelly, J. A., and Chimwaza, G. (2020). A systematic review of employment outcomes from youth skills training programmes in agriculture in low- and middle-income countries. *Nat. Food*, 1(10):605–619.
- McKenzie, D., Assaf, N., and Cusolito, A. P. (2017). The additionality impact of a matching grant programme for small firms: Experimental evidence from Yemen. *Journal of Development Effectiveness*, 9(1):1–14.
- Mgendi, G., Mao, S., and Qiao, F. (2021). Is a training program sufficient to improve the smallholder farmers' productivity in Africa? Empirical evidence from a Chinese agricultural technology demonstration center in Tanzania. *Sustainability*, 13(3):1527.
- Miguel, E. and Mobarak, A. M. (2022). The economics of the COVID-19 pandemic in poor countries. *Annual Review of Economics*, 14:253–285.
- Mishra, N., Tiwari, A., Joshi, M. D., Gaurav, Kumar, D., and Misra, V. K. (2024). Assessing the impact of agricultural subsidies on farm profitability and sustainability. *J. Exp. Agric. Int.*, 46(8):323–336.

- Morton, J. (2020). On the susceptibility and vulnerability of agricultural value chains to COVID-19. *World Development*, 136:105132.
- Mullahy, J. and Norton, E. C. (2024). Why transform y ? the pitfalls of transformed regressions with a mass at zero. *Oxf. Bull. Econ. Stat.*, 86(2):417–447.
- Nakano, Y. and Magezi, E. F. (2020). The impact of microcredit on agricultural technology adoption and productivity: Evidence from randomized control trial in Tanzania. *World Development*, 133:104997.
- Nguyen, L., Russ, J., and Triyana, M. (2023). The effect of agricultural input subsidies on productivity. *World Bank Policy Research Working Paper*, 10399.
- Pandey, B. D., Ngwe Tun, M. M., Pandey, K., Dumre, S. P., Nwe, K. M., Shah, Y., Culleton, R., Takamatsu, Y., Costello, A., and Morita, K. (2022). How an outbreak of COVID-19 circulated widely in Nepal: A chronological analysis of the national response to an unprecedented pandemic. *Life*, 12(7):1087.
- Paudel, G. P., Khanal, A. R., Rahut, D. B., Krupnik, T. J., and McDonald, A. J. (2023). Smart precision agriculture but resource constrained farmers: Is service provision a potential solution? Farmer's willingness to pay for laser-land leveling services in Nepal. *Smart Agricultural Technology*, 3(100084):100084.
- Raitzer, D. and Batmunkh, O. (2022). Impact evaluation of support to collective action for agricultural value chain development in Nepal. *Asian Development Bank Economics Working Paper Series No. 661*.
- Saha, A., Sabates-Wheeler, R., and Thompson, J. (2022). Insights into smallholder capacity for agricultural commercialisation: Evidence from four African contexts. *Eur. J. Dev. Res.*, 34(4):1757–1802.
- Sberro-Kessler, R. (2019). How can matching grants in agriculture facilitate access to finance? Lessons learned from World Bank Group's experience. Report, World Bank, Washington, DC.
- Stewart, R., Langer, L., Da Silva, N. R., Muchiri, E., Zaranyika, H., Erasmus, Y., Randall, N., Rafferty, S., Korth, M., Madinga, N., and de Wet, T. (2015). Effects of training, innovation and new technology on African smallholder farmers' economic outcomes and food security. *3ie Systematic Review 6*.

- Tabe Ojong, M. P. J. R., Hauser, M., and Mausch, K. (2022). Does agricultural commercialisation increase asset and livestock accumulation on smallholder farms in Ethiopia? *J. Dev. Stud.*, 58(3):524–544.
- Tamang, S., Paudel, K. P., and Shrestha, K. K. (2014). Feminization of agriculture and its implications for food security in rural Nepal. *Journal of Forest and Livelihood*, 12(1):20–32.
- Teklewold, H. (2021). How effective is Ethiopia's agricultural growth program at improving the total factor productivity of smallholder farmers? *Food Secur.*, 13(4):895–912.
- Tiwari, K. R., Nyborg, I. L., Sitaula, B. K., and Paudel, G. S. (2008). Analysis of the sustainability of upland farming systems in the middle mountains region of Nepal. *International Journal of Agricultural Sustainability*, 6(4):289–306.
- Tripathi, H. G., Smith, H. E., Sait, S. M., Sallu, S. M., Whitfield, S., Jankielsohn, A., Kunin, W. E., Mazibuko, N., and Nyhodo, B. (2021). Impacts of COVID-19 on diverse farm systems in Tanzania and South Africa. *Sustainability*, 13(17):9863.
- van der Heijden, J. (2024). Unravelling programme success and complex causation in agricultural research for development (AR4D): A systematic and comprehensive literature review. *Agric. Syst.*, 215(103851):103851.
- Waddington, H., Snilstveit, B., Hombrados, J., Vojtkova, M., Phillips, D., Davies, P., and White, H. (2014). Farmer field schools for improving farming practices and farmer outcomes: A systematic review. *Campbell Systematic Reviews*, 10(1):i–335.
- Wesz Junior, V. J., Piras, S., Grisa, C., and Ghinoi, S. (2024). Agri-food policies and family farms' commercialization: Insights from Brazil. *Sustainability*, 16(24):11102.
- World Bank (2025). Rural population (% of total population) – nepal (indicator sp.rur.totl.zs). Accessed: 2025-10-22.

Long-Term Effects of Group-Based Agricultural Support Amid COVID-19 Shocks in Nepal

This paper evaluates impacts of agricultural support in western Nepal and whether it strengthened resilience to COVID-19 disruptions. From 2014 to 2022, farmers received varying combinations of training, input subsidies, asset support, and credit, channeled through groups. Two-way fixed effects regressions with inverse probability weighting are applied to household panel data from 2014, 2018, and 2022 to estimate effects. Support significantly raised crop productivity, value, sales, and income, especially support including training, asset support, or credit provision. Assistance after 2018 offset pandemic shocks, while earlier support improved lasting resilience. Effects of support in both periods are generally progressive with respect to income.

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